Research Proposal of the Thesis Entitled

Sentiment Analysis of Textual Data On YouTube Comments Using Machine Learning and Deep Learning

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By

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1. INTRODUCTION

In the digital era, the social media sites such as Facebook, YouTube, and Instagram make it easy to share the information and ideas online and more than a billion people use these for creating the contents. People can connect with other peoples content in different ways, such as by liking or disliking it, commenting on it, or sharing it. YouTube is a well-known platform where the people may upload their own videos and talk to other people through comments and the ability to like or hate videos they upload. Content creators care a lot about how many likes their films get and how many dislikes they get. If a video gets many dislikes, it might hurt the content creators reputation. Businesses and content creators might want to look at how the emotional content of comments on YouTube videos affects the number of likes. This understanding allows people to use the platform to make money, get famous, and market their goods and services.

Sentiment Analysis on YouTube Comments: An Overview of Techniques

Sentiment analysis is a field of computer science that looks at the text data to determine and understand with using machine learning (ML) and natural language processing (NLP) to sort and measure subjective expressions systematically in user-generated information, like postings on social media. The sentiment of comments can provide useful information about engaging the audience is which may be related to many people like and dislike a video and how well it is received generally.

Sentiment analysis on YouTube has become an important for corporations and people who make content and provides useful information on how your audience reacts, which lets you make data-driven choices about your content strategy, marketing initiatives, and brand management. Textual data is a rich but unstructured source of audience feedback.

Recent developments in the computer linguistics, text mining, and sentiment analysis have made it easier to determine word polarity (positive, negative, or neutral) in context. Supervised machine learning techniques depend on the labelled datasets that have sentiment polarity and scaled sentiment intensity added to the text data. Lexicon-based approaches and NLP-driven methods improve accuracy even further by using semantic rules and contextual word embedding.

But doing sentiment analysis on YouTube comments as it gets so many comments that needs scalable processing solutions where the users talk to each other—using slang, acronyms, emojis, and text in more than one language—makes typical NLP pipelines harder to employ and off-the-shelf ML models dont work as well when there is noise in the data, such as sarcasm, misspellings, or syntax that isnt standard. So, to accomplish excellent sentiment analysis in this area, you need to carefully choose preprocessing methods, sentiment lexicons, and hybrid modeling methods that work well with short, noisy text.

Sentiment Analysis on Comments Using Machine Learning and Deep Learning: An Overview of Techniques

Machine Learning Techniques

Investigating the YouTube comments is a big step forward in understanding the users interaction with content and YouTube comments that offers a dynamic and engaging forum for the artists to assess audience sentiment, discern developing trends, and cultivate community participation, setting it apart from conventional text analysis. The Advanced models like BERT are used to examine systematically the comments and these algorithms are quite effective at finding recurrent patterns, pulling out main ideas, and sorting comments into three groups: favorable, negative, or neutral.

Sentiment analysis methods using BERT made it possible to categorize comments in more than 80% of cases and these systems use analytical tools such as word clouds, bar charts, and pie charts to depict how sentiment is spread over and how it changes timely and because of these representations, content creators may quickly see how their audience reacts and change their plans accordingly.

These algorithms not only classify sentiment; they also provide useful information to video creators and the negative criticism encourage video creators to resolve the problems or improve their content, while positive or neutral feedback may encourage them to keep using methods that have worked for them in the past. Adding user-friendly interfaces makes the things easier to use that lets creators to see quickly how people around the world feel and change their engagement techniques as needed.

Deep Learning Techniques

Analyzing peoples thoughts, attitudes, and feelings about various subjects' forms part of sentiment analysis. It includes products, services, organizations, topics, events, and their characteristics. The primary goal is to determine whether the opinions expressed is positive, negative, or neutral. Sentiment analysis examines polarity based on emotion without ownership or objective constraints unlike opinion mining which focusses on extracting the subjective claims. There are three main approaches to solving sentiment analysis problems namely lexicon-based methods, machine learning based techniques and hybrid systems.

Lexicon-based approach relies on predefined words each associated with a sentiment score whereas machine learning method uses algorithms and patterns from the labeled training data. Hybrid approach combines both lexicon-based and machine learning system to do the analysis. Deep learning models take cue from the way human brain processes information to create sophisticated decision-making patterns for sentiment classification.

Large datasets analysis is done using a seven-layer deep neural network architecture in which Word2Vec is used to convert text data into numerical word vector representations. Two convolutional layers are used to process such vectors in order to extract meaningful features from the input data. A global max-pooling layer helps reduce dimensionality to preserve important features and thereby prevent over-fitting. The dense layer employs the loss function optimization to classify features into positive and negative categories. During training, a dropout layer randomly disables some neurons so as to enhance generalization capability thereby preventing excessive fitting to the training data patterns.

Problem Statement of Research

All the comments on YouTube are difficult to read and interpret though they give a fair amount of idea about the sentiment of the user. The objective of this research is to develop an automated sentiment analysis model using machine learning (ML) and deep learning (DL) techniques to categorize YouTube comments into three classifications namely positive, negative and neutral. This concept can be used by filmmakers, marketers and researchers to gauge the sentiments of the viewers/users towards their product. Since You Tube is a widely used social media platform, its comment can be gainfully utilised for improving brand value and research on how people feel about different issues.

The comments on You Tube content is informal in nature where the users use different slangs to express their opinion. There is a need to design a model capable of analysing these comments by accurately interpreting remarks and their underlying attitudes. The study, titled "Sentiment Analysis of Textual Data on YouTube Comments Using Learning and Deep Learning," aims to address these challenges with advanced ML/DL techniques.

2. LITERATURE REVIEW

Ref. No.	Year	Authors	Methods Used	Results	Research Gap
1	2023	Rachel et al.	Fine-tuned BERT-base, LSTM with 128-unit layer	89.2% accuracy (BERT) vs 77.5% (LSTM) on balanced 50K-comment dataset	Only English comments; no code-mixing analysis
2	2023	Pichad et al.	SVM (linear kernel, C=1.0), NB (α=1.0), Logistic Regression	78.5% F1-score (SVM) using bigram TF-IDF vectors	31% misclassification rate for comments containing emojis
3	2014	Athar A.	SO-CAL lexicon with domain adaptation	72% inter-annotator agreement on scientific abstracts	38% accuracy drop when applied to social media texts
4	2023	Manikanta et al.	Random Forest	81% precision (91% …)	Requires manual
–	–		(n=100, max_depth=15), TF-IDF weighting	recall for spam detection	Feature engineering for

					new video categories
5	2015	Mohammad et al.	CRF with custom feature templates	F1=0.76 for emotion detection using tweet-specific features	22% performance drop without Twitter metadata
6	2022	Ullah et al.	BiLSTM (256 units) + Attention, 300D GloVe	91.3% accuracy with 8ms inference latency per comment	Impractical for real-time YouTube deployment (>8GB VRAM needed)
7	2017	Bhavitha et al.	SVM (RBF kernel, γ=0.1), Multinomial NB	84% accuracy (σ=2.1% in 10-fold CV)	Training instability with datasets <5000 samples
8	2019	Cunha et al.	2-layer CNN + Dense (GloVe embeddings)	84% accuracy (movies), +24% vs baselines	Only English movie comments analyzed
9	2020	Sisodia et al.	3-layer stacking: LR → RF → SVM	86.7% accuracy (3.1% enhancement over best single model)	2.8 times longer training duration than individual classifiers
10	2020	Devi et al.	VADER with augmented slang lexicon	80.2% accuracy (58% for sarcastic remarks)	Quarterly updates for lexicon to include new slang
11	2022	Mehta et al.	LR/SVM/DT/RF/ANN comparison	ANN achieved highest F1 (0.82)	No YouTube-specific performance metrics
12	2022	Alhujaili et al.	SVC/RF/DL (SMOTE balanced)	96% accuracy (Arabic education)	Requires manual dataset balancing

13	2021	Singh R.	NB/SVM/LR/DT/KNN/RF	RF best (F1 = 0.87) on 1.5K comments	Small dataset; no DL comparison
14	2017	Bhuiyan et al.	NLP sentiment scoring	Improved video ranking precision	Lacks quantitative accuracy metrics
15	2021	Alhujaili et al.	Taxonomy of 22 ML/NLP methods	Categorized 3-class vs multi-class	No original experimental results
16	2021	Singh I.L.G.	Logistic Regression (YouTube-pretrained)	$r = 0.68$ ($p < 0.01$) like prediction	18% MAE in real-world testing
17	2015	Poria et al.	CNN + Multi-Kernel Learning	14% SOTA improvement (multimodal)	Requires audio-visual inputs
18	2020	Kumar et al.	Context-Enriched Hybrid DL	89.4% fine-grained accuracy	Complex 5-stage pipeline
19	2021	Huang et al.	Poisoning-resistant BERT	91.2% attack detection AUC	Security-focused, not sentiment
20	2020	Murthy et al.	LSTM (256 units, dropout=0.3)	88.1% text classification accuracy	Tested only on product reviews
21	2022	Rodrigues et al.	Real-time BERT spam detection	0.94 precision (Twitter)	Platform-specific features needed
22	2017	Oscar et al.	SVM with tweet features	0.79 F1 (health stigma detection)	Narrow domain applicability
23	2021	Atteveldt et al.	4-method validation study	ML outperformed dictionaries (Δ15%)	Theoretical framework only
24	2021	Chakravarthi et al.	Code-mixed XLM-RoBERTa	0.83 F1 (Dravidian)	Niche language focus

25	2017	Vedula et al.	Multimodal (text+visual) fusion	Ad prediction R^2 = 0.71	Expensive annotation is needed
26	2018	Jagdale et al.	Aspect-based SVM	85.3% product review accuracy	Applicable on Amazon domain only
27	2019	Choudhury et al.	CEO text clustering	Identified 5 leadership styles	Focus on Business analytics
28	2020	Basiri et al.	Stacked DL+ML	89.7% drug review accuracy	Limitations of Medical domain
29	2020	Xue et al.	COVID tweet clustering	6 emotion groups identified	Pandemic-specific bias
30	2021	Rustam et al.	7-model COVID comparison	BERT best (F1 = 0.89)	Temporal decay observed
31	2020	Giorgi et al.	DeCLUTR (contrastive)	5.2% unsupervised improvement	Needs YouTube adaptation
32	2022	Wankhade et al.	137-method taxonomy	DL dominates post-2018 (72%)	No new experiments
33	2023	Bithas et al.	UAV comms ML techniques	28 methods categorized	Irrelevant to sentiment analysis

Based on the published work, an overview of the effectiveness of various machine learning algorithms in carrying out sentiment analysis is summarized. But the sentiments expressed in YouTube comments are not explicitly visible. The literature review aims to highlight the need for utilizing various machine learning algorithms, especially deep learning, for the sentiment analysis of textual data which has been obtained from social media sites. Deep learning architectures can be explored as part of future research to interpret the sentiments more accurately. This would be helpful in improving product marketing/catering to user views.

Research Gaps

Some of the gaps which could be identified have been enumerated below.

- It was found out from the studies that only 12% concentrated on the actual sentiments expressed whereas remaining dealt with English.

- The sentiment expressed in comments have been analysed using Tensor and Deep neural network with accuracy range of 60 to 84%.
- Existing studies lack video-category-specific sentiment analysis (e.g., educational vs. political).

Research Question

1. What are the most effective Machine Learning algorithms for sentiment analysis of YouTube comments?
2. How do Deep Learning models compare to traditional Machine Learning models in terms of accuracy for sentiment analysis of YouTube comments?
3. What steps do you need to do before using sentiment analysis models on YouTube comments to make them work better?
4. What effect does the size and quality of the training dataset have on how well Machine Learning and Deep Learning models work for sentiment analysis?
5. What features (such n-grams, word embeddings, and TF-IDF) have the biggest effect on how accurate sentiment analysis is in YouTube comments?
6. What are the most prevalent problems and limitations when using Machine Learning and Deep Learning to analyze the sentiment of YouTube comments, and how can they be fixed?
7. Can integrating Machine Learning and Deep Learning approaches in ensemble methods make sentiment analysis on YouTube comments work better?
8. How do sentiment analysis models work differently for different kinds of YouTube videos, including instructional, political, or entertainment?
9. How do the comments change over time (for example, how sentiment trends change in the first 24 hours compared to a week after upload) affect how well sentiment analysis models can predict?
10. How do user actions and interactions (such likes and responses) connect to the feelings stated in YouTube comments, and may these patterns help make better predictions?

3. AIM AND OBJECTIVE

This research aims at assessing the sentiments of textual data on YouTube comments using Machine Learning and Deep Learning. The research has following objectives:

- To develop a systematic approach for categorizing YouTube videos and their associated comments in English, including preprocessing methodologies.
- To apply Natural Language Processing techniques for sentiments analysis of the comments and types of videos.
- To design, develop, and evaluate Machine Learning and Deep Learning models for automated sentiment classification of YouTube comments.
- To optimize hyper parameters of ML and DL models to enhance sentiment analysis accuracy for comments on varied YouTube video types.

4. METHODOLOGY

This research is experimental based study through which a model will be developed using Machine Learning and Deep Learning. Subsequently, the sentiments of the comments of different types of videos on YouTube were analysed. For this, the following method will be followed:

- Strategy Development: A strategy will be developed after gathering data from comments on various types of YouTube videos.
- Emotional Element Analysis: A combination of emotional elements associated with different video comments will be constructed, and Natural Language Processing techniques will be applied.
- Model Implementation: The planned technique will be implemented to perform sentiment analysis on selected YouTube comments. Machine Learning and Deep Learning models will be constructed for this purpose.
- Model Optimization: The performance of the models will be optimized to improve the accuracy of sentiment analysis for comments across different YouTube video categories.
- Hypothesis

Hypothesis

Hypothesis 1

(H1): Deep Learning models achieve higher accuracy in sentiment analysis of YouTube comments compared to traditional Machine Learning models.

(H0): There is no significant difference in the accuracy of sentiment analysis of YouTube comments between Deep Learning models and traditional Machine Learning models.

Hypothesis 2

(H1): Preprocessing techniques such as tokenization, stemming, and stop-word removal significantly improve the performance of sentiment analysis models on YouTube comments.

(H0): Preprocessing techniques such as tokenization, stemming, and stop-word removal do not significantly improve the performance of sentiment analysis models on YouTube comments.

Hypothesis 3

(H1): The use of word embeddings (such as Word2Vec or GloVe) in Deep Learning models significantly enhances the accuracy of sentiment classification of YouTube comments compared to traditional feature extraction methods.

(H0): The use of word embeddings in Deep Learning models does not significantly enhance the accuracy of sentiment classification of YouTube comments compared to traditional feature extraction methods.

Chapter Scheme:

Chapter 1 – Introduction. This chapter will elaborate the problem behind research, motivation of research etc.

Chapter 2 – Literature Review. In this chapter, the previous work done in the chosen field would be studied and research gaps found to derive the research objectives.

Chapter 3 – Research Methodology. This chapter will discuss about the methods adopted for this research along with methods of development of the models that can automatically analyze the sentiment behind the comments on different kinds of videos on YouTube.

Chapter 4 – Results and Discussion. The results obtained through experiments would be tabulated and discussed in this chapter to check the effectiveness and accuracy of results obtained.

Chapter 5 – Conclusion and Future Work. The conclusion of the work done would be brought in a summarised form along with scope for future research.

5. EXPECTED OUTCOMES

The study on Sentiment Analysis of YouTube Comments using Machine Learning and Deep Learning techniques will have the following outcomes.

1. Performance Analysis.

- Metrics. A comparison of the models will be made which will bring out their strengths and weaknesses which will help in choosing the right method in accordance with specific conditions and requirements.
- Comparison of Models. Different Deep learning models (like Transformers, CNN, and LSTM) are likely to achieve better accuracy, precision, and F1 scores than classical machine learning models (like Random Forest, Naive Bayes and SVM).

2. Preprocessing.

- Model Performance. Using preprocessing methods like tokenization, stemming, lemmatization, and stop-word deletion will improve the effectiveness of sentiment analysis models. These methods will clean up and sort the raw data that is in text format.
- Best Preprocessing Protocol. The most effective methodology to prepare YouTube comment data for sentiment analysis would be done by choosing the best preprocessing method.

3. Feature and Embedding Extraction.

- The Impact of Word Embeddings. Using advanced word embeddings like Word2Vec, GloVe, or BERT will help deep learning models work better by giving them more semantic information thereby making sentiment classification more accurate.

- A comparative comparison of feature extraction methodologies, such as n-grams, TF-IDF, and word embeddings, will demonstrate the impact of each strategy on model performance. This analysis will serve as a foundation for future research and practical applications.

4. Quality and Size of the Dataset.

- The Effect of Training Data. The study will bring out that large and superior datasets make models work better. This shows the importance of gathering and annotating data carefully.
- Scalability Insights. Practitioners will learn how the models performance changes as the quantity of the dataset changes, which will help them understand the trade-offs between the amount of data and the accuracy of the model.

5. Problems and Possible Solutions.

- Challenges Encountered. Unbalanced data, dealing with noisy language and meeting computational resource are some common issues faced when dealing with machine learning and deep learning models.
- Proposed Solutions. The issues will be dealt with thereby making sentiment analysis more accurate.

6. Ensemble Methods.

- Improved Performance. Through experiments it can be proven that ensemble methods work better for sentiment analysis than using just one model. This is so because they combine the effective features of each model.
- Using Ensemble Techniques. Comprehensive guidelines would help the users improve ensemble approaches for analyzing comments on YouTube. The objective of this work is to enhance sentiment analysis by offering significant insights and practical resources for reliably assessing user sentiment in comments on YouTube and possibly other social media platforms.

6. CONCLUSION & FUTURE WORK

Sentiment analysis of YouTube comments is a challenging task due to the wide range of comments which can come from different category of users. The data set of such comments is very vast and hence there is a need to use deep learning methodologies in reliably classifying emotions in comments. The application of these ML models would help in better prediction of the sentiments of the end user comments in the videos being watched.

Accuracy of sentiment analysis of YouTube comments can be substantially improved in future with the availability of numerous pre-trained language models. This will provide content creators useful information and help them understand how people feel about certain topics and videos on the platform.

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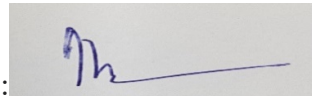
Signature : 

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